A Method for Aircraft Concept Selection Using Multicriteria Interactive Genetic Algorithms

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Abstract

The problem of aircraft concept selection has become increasingly difficult in recent years as a result of a change from performance as the primary evaluation criteria of aircraft concepts to the current situation in which environmental effects, economics, and aesthetics must also be evaluated and considered in the earliest stages of the decision-making process. This has prompted a shift from design using historical data regression techniques for metric prediction to the use of physics-based analysis tools that are capable of analyzing designs outside of the historical database. The use of optimization methods with these physics-based tools, however, has proven difficult because of the tendency of optimizers to exploit assumptions present in the models and drive the design towards a solution which, while promising to the computer, may be infeasible due to factors not considered by the computer codes. In addition to this difficulty, the number of discrete options available at this stage may be unmanageable due to the combinatorial nature of the concept selection problem, leading the analyst to arbitrarily choose a sub-optimum baseline vehicle. These concept decisions such as the type of control surface scheme to use, though extremely important, are frequently made without sufficient understanding of their impact on the important system metrics because of a lack of computational resources or analysis tools. This paper describes a hybrid subjective/quantitative optimization method and its application to the concept selection of a Small Supersonic Transport. The method uses Genetic Algorithms to operate on a population of designs and promote improvement by varying more than sixty parameters governing the vehicle geometry, mission, and requirements. In addition to using computer codes for evaluation of quantitative criteria such as gross weight, expert input is also considered to account for criteria such as aeroelasticity or manufacturability which may be impossible or too computationally expensive to consider explicitly in the analysis. Results indicate that concepts resulting from the use of this method represent designs which are promising to both the computer and the analyst, and that a mapping between concepts and requirements that would not otherwise be apparent is revealed.

I.   Introduction

IN his textbook *Aircraft Design: A Conceptual Approach*[1], Raymer depicts an ideal model of the aircraft conceptual design process in a sketch called the "Design Wheel," where the generation of the design concept, or the famous "back of the envelope" drawing, is depicted as an iterative process with multiple feedback loops in which the requirements and engineering analysis are used to refine the configuration.

In reality, several of the feedback loops shown in this figure are omitted for various reasons. Historically, the design process progresses in a more serial fashion and has usually started with requirements specification, where questions such as "how fast," "how far," and "how much" are asked and then answered. These requirements drive the engineers to determine the type of vehicle concept that would be appropriate given the requirements and to consider questions such as which technologies should be included in the design or whether a canard or traditional tail should be installed. The vehicle then undergoes a process known as sizing, in which the geometry and weight are scaled in an iterative process until the vehicle is capable of performing the design mission. Finally, trade studies are used to optimize the configuration by generating carpet plots and examining the impact of the vehicle's characteristics on its performance and weight.

This process has obviously worked reasonably well, as evidenced by the thousands of airplanes in the sky at this very moment. In recent years, however, the aircraft concept selection problem has become increasingly difficult as numerous additional factors are included in the set of primary evaluation criteria of aircraft concepts. While performance and weight were once viewed as pre-eminent, factors such as environmental effects, economics, and aesthetics have become equally important. Revolutionary vehicles such as supersonic transports may also be constrained by factors including sonic boom loudness and cruise emissions. The addition of these conflicting requirements has forced designers to consider novel concepts that differ greatly from previous aerospace vehicles because traditional designs are simply not capable of meeting all project goals and constraints.

II.   MOTIVATION

The need for a more rigorous conceptual design method when designing revolutionary systems becomes apparent after examination of the ``Knowledge-Cost-Freedom Curve", Figure 1. This diagram depicts the designer's relative amount of knowledge about the design under study, the amount of freedom the designer has to modify the system, and the cost committed, which are all a function of time in the design process. It also shows the unfortunate situation that the decisions made during the earliest stages of the design process are typically made with very little hard information despite the fact that they have an enormous impact on the design effort's outcome.
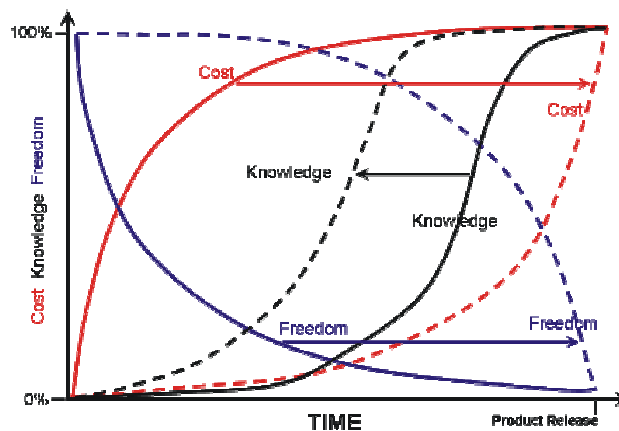

Figure 1 - Knowledge-Cost-Freedom Curve

If the system being designed is similar to those produced in the past, this lack of knowledge is not a major difficulty because the analyst is able to incorporate historical data and past design experience into the decision-making process. Many references have compiled statistics on previously manufactured aircraft and used these results

to create "rule of thumb" charts, such as those of Figure 2, which provide guidance to the design team by giving suggestions about the appropriate configuration choice as a function of the design requirements.
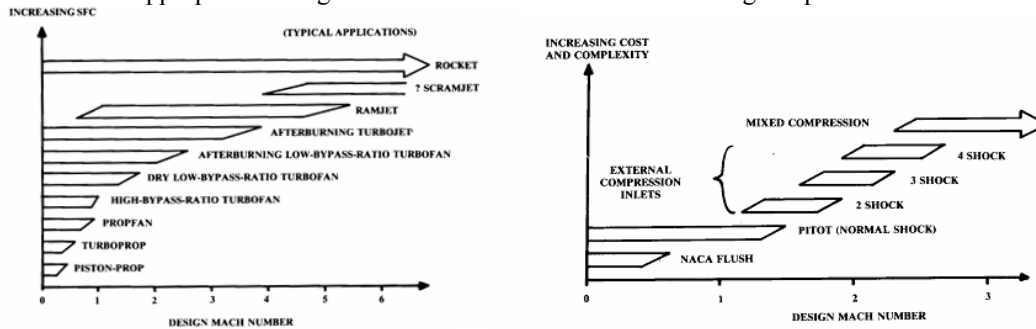

Figure 2 - "Rule of Thumb" example charts [1]

When revolutionary systems are being considered, however, the design team may have little experience with the new class of vehicle and there may be no historical data available to guide the decision-making progress. These uncertainties can lead to incorrect decisions early on and large cost increases or project failure downstream. History has shown that these failures occur most frequently when the system requirements are greatly different than those of previously designed systems because no "rules of thumb" have yet been developed to guide the design team.

A. Obstacles to an integrated conceptual design process

Many researchers and engineers have recognized deficiencies in the conceptual design process and developed a wide variety of methods to provide more information to the decision makers earlier in the design cycle. The majority of these efforts have focused on automating the design process by using computers. This work has helped to create a new field of study, Multidisciplinary Design Optimization (MDO), but despite the large amount of literature available on MDO techniques, not a single aircraft in service has been designed using these methods. Although there are a plethora of reasons for this lack of application, the following ones are judged by the author to be the most significant obstacles to the widespread application of MDO techniques to aircraft design by industry.

1. Difficulty of establishing relevant criteria

In the heyday of the aerospace industry, engineers designed with the concept of "farther, faster, better" in mind – performance was the ultimate objective. In today's environment, the situation is less well defined, and factors such as economics, environmental impact, and time to market are equally-- if not more-- important than achieving the best possible performance.

This paradigm shift makes it much more difficult to determine which aircraft is "best" overall, because most of these objectives are conflicting: a faster airplane usually costs more than a slow one; an airplane with a greater range will be heavy; and so on. Figure 3, the classic illustration of this principle, shows the ideal airplane from the perspective of each engineering discipline.
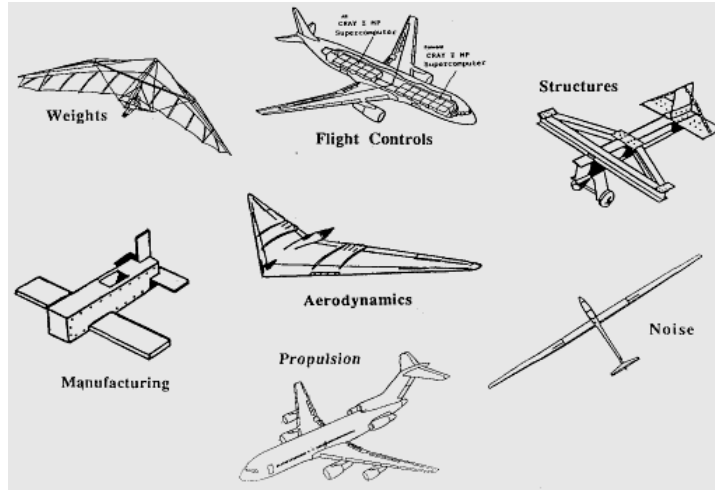
Figure 3 - The "best" airplane from a disciplinarian's view [2]

None of these concepts are actually ideal from a systems standpoint because a successful vehicle will be the result of appropriate compromises between the relevant objectives. The difficulty rests in determining "the best" compromise, and formulating a single objective that encompasses the designer's preference. Traditionally, the engineer forms an overall evaluation criterion by aggregating the different objectives through the use of a weighted sum. While this method has been used with success, but it frequently requires many optimization runs because it is difficult for the engineer to appropriately assign weights to the objectives, and this difficulty results in an "optimal" design that does not really satisfy the decision-maker's wishes.

2. Difficulty in quantifying many important metrics

Every model used to aid in conceptual design is by definition a simplified representation of reality. Optimizers have an amazing tendency to "break" computer analyses: they will quickly exploit the assumptions used in the model in an effort to wring every last ounce of capability from the vehicle. This results in vehicles that appear to be optimal to the optimizer, but in reality are impractical. Kroo[2] gives an example in which the optimization of a Cessna resulted in a lighter vehicle that in fact was not airworthy since the optimizer exploited the analysis's simplified stability calculations (Figure 4).
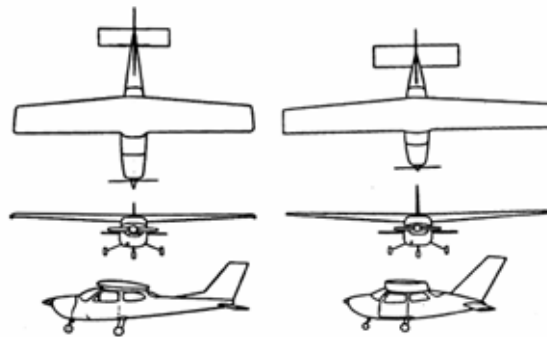

Figure 4 - "Optimized" Cessna that takes advantage of a lack of stability-calculation fidelity [2]

In some cases, there may be no available model to quantify important decision criteria. Metrics such as manufacturability, maintainability, and aesthetics are largely subjective, and are designed into a system "by eye". When the task of design is left up to a computer, these parameters are ignored, which once again, leads to unsatisfactory results.

3. Computational expense of analyses

Many researchers have devoted a large amount of effort to improve the physics-based models in order to avoid errors resulting from oversimplification. This effort has resulted in more accurate methods, including Computational Fluid Dynamics and Finite Element Analysis, but, unfortunately, the computational expense of these codes has prevented their widespread use in design, because optimization techniques typically require a large number of function calls. Some novel approaches like the Adjoint method[3] have found ways around this difficulty by using alternate problem formulations, but they are typically only applicable to the sizing and parameter optimization problems because they require continuous and well behaved objective functions.

4. The curse of dimensionality

Before the advent of modern optimization techniques, designs were traditionally "optimized" through the use of carpet plots, in which the objective (typically gross weight) was plotted as a function of two design variables, such as thrust- to- weight and wingloading. By superimposing the constraints, the analyst could find the combination of the two design variables that resulted in the lightest feasible design. However, visualization limitations prevented the analyst from exploring the impact of more than two variables at a time, resulting in designs that were not truly optimal.

MDO techniques promised to eliminate this restriction, but have in fact only alleviated it. Because the number of function evaluations required to find an optimal solution usually increases as an at best quadratic function of the number of variables, the designer is forced to limit the number of parameters that are optimized, typically to less than twenty design variables. The designer is therefore forced to choose fix potentially significant parameters at nominal values, resulting in sub-optimal performance.

5. "Noisy" and discontinuous objective functions

Most efficient MDO techniques have relied upon gradient information in some form. When available, the gradient allows for rapid solution convergence, but these methods are not applicable to the synthesis problem when the variables consist not only of continuous parameters such as wing sweep or area but also variables such as the number of engines or type of tail to use.

Even when dealing with only continuous input variables, gradient based techniques may have problems owing to noisy objective functions. Since many of the models used as objectives in MDO problems require internal iteration to calculate performance, the output may not be a smooth function of the inputs. Calculus-based optimization techniques are unable to cope with these problems because they are unable to escape local minima.

III.   Design Methods

In order to tackle the concept selection problem, researchers and engineers in many domains have turned to Genetic Algorithms[4], which employ Darwin's "survival of the fittest" principal and use nature-inspired genetic operators such as crossover and mutation to promote favorable change in the population. The benefits typically associated with Genetic Algorithms are the ability to handle mixed continuous/discrete design spaces, the ability to solve global optimization problems that have numerous local minima, and the fact that no gradient information is required. Another benefit is the fact that the number of function calls required for convergence usually increases approximately linearly with the number of input variables in contrast with the polynomial or exponential increase required by many other optimization methods.

These advantages have resulted in many examples of application by the engineering community, including the design of robots[5], hydropower plants[6], and circuit boards[7]. Genetic Algorithms have also been used for aircraft design problems, but previous efforts have been limited to either conceptual level studies with a small number of alternatives and simplified analyses[8] or preliminary design parameter variation problems[9] due to the typically large number of function evaluations required for solution convergence and the associated computational expense.

Genetic Algorithms effectively deal with noisy objective functions and can be used for problems with a large number of inputs, but the classical GA does not address the first three difficulties discussed in the previous section: the difficulty of establishing relevant criteria, quantifying critical metrics, and optimizing computationally expensive analyses. These deficiencies have inspired several enhancements to the original algorithm including multi-objective GAs, interactive GAs, and parallel GAs that have proven effective for problems that are traditionally difficult to optimize.

B. Multiobjective GAs

In engineering design, there are almost always multiple criteria that must be considered during the concept selection process. Objectives such as weight, cost, and speed must be balanced versus each other to find that "right mix" that will result in a successful program. Traditionally, these problems were handled by creating an aggregate objective function and using a weighted sum approach. This method has many drawbacks, since it is often very difficult to numerically quantify how important the objectives are relative to each other, resulting in designs which do not really best meet the users' goals.

Multiobjective Genetic Algorithms (MOGAs) attempt to solve this problem by using the concept of Pareto optimality to find non dominated solutions. A solution is said to be non-dominated when there is no other solution in the space which is better with regards to all decision variables. The set of non-dominated solutions, or Pareto front, makes up a hypersurface along which improvement in one objective requires a sacrifice in another (Figure 5a).
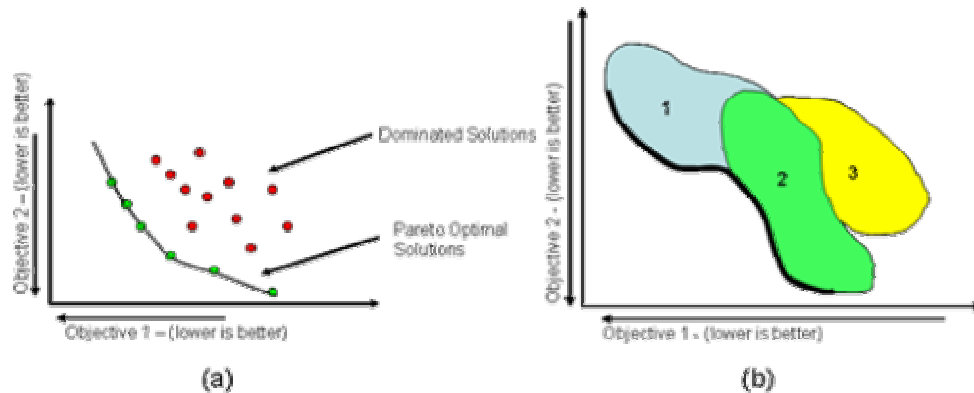

Figure 5 - Pareto and s-Pareto optimality

Once this front has been found, the engineer can use it to explore the relationship between the objectives so that intelligent decisions can be made. In conceptual design, one is often interested in determining which configuration makes the most sense in a given area of the requirements space. The s-Pareto[10] frontier (Figure 5b) is a visualization of this type of result, and clearly shows the relationship between objectives and configurations. In the notional example of Figure 5b, concepts 1 and 2 make up the Pareto front, while concept 3 is completely dominated and would quickly be forced out of the population due to selection pressure.

Several modifications to the conventional GA such as the Strength Pareto Evolutionary Algorithm[11] have gained widespread acceptance for use in this type of multi-objective problem but recent research[12] has shown that while they work very well for two or three objective problems, they all perform very poorly for problems where there are a large number of conflicting objectives. This deficiency is largely due to the requirement for an exponential population size increase as the number of objectives increases in order to maintain sufficient selective pressure, since as the number of simultaneous objectives increase the proportion of the population that is non-dominated grows exponentially.

C. Interactive GAs

In many cases during the design process the analyst is interested in criteria which are either non-quantifiable or for which there are no available numerical models. Examples of the former include metrics such as aesthetics or manufacturability while the latter includes difficult to calculate metrics like aeroelasticity and flutter performance. If these important metrics are neglected during design and optimization, the resulting concepts typically exploit these omissions, resulting in vehicles that appear promising to the computer but seem ridiculous to the human analyst.
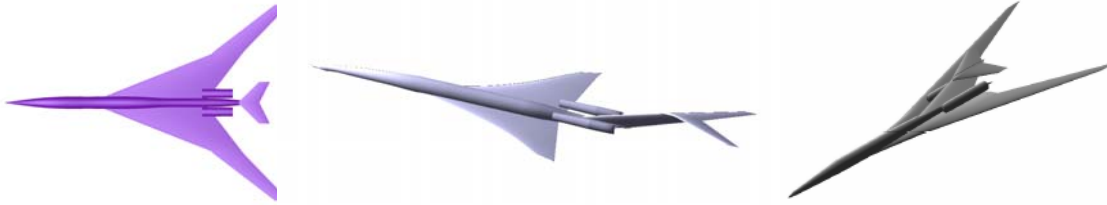

Figure 6 - Infeasible concepts resulting from numerical optimization (from References 13 and 14)

Designers in other domains such as the fashion, art, and music industries have no quantifiable criteria that can be used to rate concepts, and have developed Interactive Genetic Algorithms (IGAs) in which solution fitness is calculated solely based on subjective input (Figure 7). Population members are displayed in a graphical user interface, and at the end of each generation the user is asked to rank the presented concepts based upon their preference.

Though there have been many applications, Takagi[15] has identified several difficulties with current IGA practice. He identifies the primary problem as the one of human fatigue, since it can be very tedious to manually evaluate the large number of design alternatives required by IGA techniques. Research has indicated that IGA operators typically get bored with selecting designs after about twenty generations. At this point, the operator's decisions become more random, and the rate of increase in solution quality slows dramatically. Several researchers have proposed methods including neural network[18] or k-nearest neighbor[17] prediction to ease the burden on the human operator, but the benefits of these approaches remain unclear. Another promising method to reduce the workload is to limit the number of fitness levels available to choose from, though this increases quantization noise and may delay convergence in later generations[16].

Figure 7 - Example interactive evolutionary design environments (from References 19 and 20)

D. Parallel GAs

One of the most frequent criticisms of Genetic Algorithms is that they typically require a very large number of function evaluations to converge to the optimum. In previous applications of GA to aircraft conceptual design, this was not much of a problem since computationally inexpensive statistical methods were usually used for function

evaluation. The problem at hand, the design of a small supersonic transport, does not readily lend itself to the use of very simplified analysis since the vehicle being studied lies outside the bounds of the historical database, necessitating the use of physics-based analysis tools for performance prediction.

One commonly used approach to accelerate GA convergence is to harness the capabilities of parallel computing by using Parallel Genetic Algorithms (PGAs). These algorithms come in two main varieties: fine- and coarse-grained. In a fine-grained PGA, multiple computers are used to evaluate the different population members' fitness values in parallel, while coarse-grained PGAs break up the population into multiple sub-populations, allowing intermittent communication between the developing groups. Research[21] has shown that coarse-grained PGAs can exhibit a super-linear speedup with the number of populations, but setting up the parallel topology can be difficult. One example of a successful coarse-grained Parallel GA is Eby's injection-island GA[22] that used multiple resolutions of analysis in parallel for the optimization of flywheels. This work employed variable fidelity analyses, using only the most accurate analysis for the ultimate fitness evaluation, while the low fidelity calculations were used to find promising candidates to inject into the high fidelity analysis' population. This optimization scheme was shown to improve convergence rate by nearly an order of magnitude compared to Holland's classical GA.

E. Heirerarchical Crossover Operator

Initial studies revealed conventional GA crossover operator was found to have very poor performance when applied to hierarchical synthesis problems due to excessive chromosome disruption. Parmee[23] encountered similar difficulties when using GAs to perform system design of a hydropower plant and developed a method known as GAANT to allow useful transfer of information between different discrete configurations, but that approach was found to be unsuitable for this type of problem where the number of alternatives was large.

This deficiency prompted the development of a new type of hierarchical crossover where a standard uniform crossover operator is used on components of the same category type (for example, if both aircraft have variable geometry wings) but the components are swapped with 50% probability if dissimilar (one parent has a canard and one a T-tail). Figure 8 depicts an example where two parents of dissimilar topologies undergo hierarchical crossover to produce two offspring. Experimental results showed that this method facilitated useful genetic information transfer with minimal gene disruption, greatly accelerating convergence.
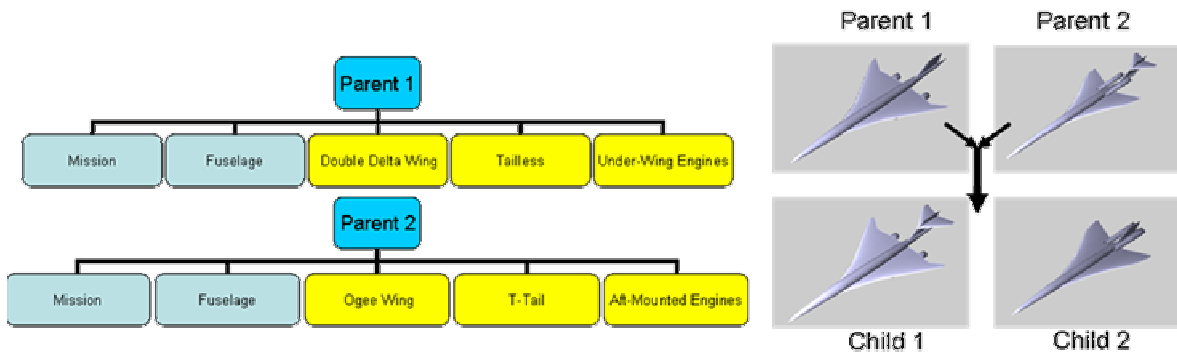

Figure 8 - Heirarchical crossover operator

Future work with this new crossover operator will involve investigating the impact of preferential selection during recombination by making it more or less likely to select genotypically similar parents.

IV.   Problem Definition

Most of the major airframe manufacturers, spurred on by the favorable market forecasts and the DARPA QSP program[24], have researched quiet supersonic airplanes, but to this point no definitive conclusion has been reached regarding what the vehicle should look like. Designs proposed by industry members and government differ in engine location, wing planform type and location, control surface layout, engine cycle, and other key defining characteristics (Figure 9).

Figure 9 – Some of the small supersonic transport concepts generated by industry

A survey of the efforts underway at NASA and in industry reveals that in addition to these physical and geometric differences, each organization has quite different goals in mind (Table 1). These differing requirements are likely a driving force behind the widely varying configurations currently being proposed.

Table 1- Small supersonic transport design requirements published by industry and government

Requirement	Aerion	Gulfstream	NASA	Raytheon	SAI
Range(nm)	4000	4800	4000-4500	5000	4000
Gross Weight(lbs*1000)	90,000	100,000	100,000	120,000	150,000
Balanced Field Length(ft)	6000	6500	6500	6000	8000
Cruise Mach #	.99/1.6	1.6-2.0	1.6-2.0	1.8	1.6-1.8
Payload	8-10 Pax	1500 lbs	6-10 Pax	6 Pax	8-12 Pax
Takeoff/Landing Noise	Stage IV	Stage IV-10 dB	Stage IV-2 dB	Stage IV	Stage IV
Length (ft)	145	140	130-140	165	130
Boom Loudness	none	.15 psf ramp	.4 psf ramp	.4 psf ramp	.3 psf ramp

The vehicle concepts discussed here and others not shown were used to establish a matrix of possible small supersonic transport configuration alternatives (Table 2). This matrix is not all-inclusive, but represents the majority of plausible configuration options for this type of vehicle. In the current work only those highlighted were considered during the genetic search due to modeling limitations and data availability.

Table 2 – Small supersonic transport concept matrix

Planform Type	Conventional	Delta	Double Delta	Ogee	Blended	Variable	Strut-Braced	Unswept NLF
Pitch Control Method	Elevons	Conventional Tail	Cacard	T-Tail	3-Surface			
Powerplant Installation	Under Wing	Fuselage Mounted	Tail Mounted					
Wing Vertical Location	Low	High	Mid					
Engine Cycle	Mixed Flow Turbofan	Variable Cycle	Flade	Turbine Bypass				
Inlet Type	Axisymmetric External	Axisymmetric Mixed	2-D Mixed					
Nozzle Type	Conventional	Mixer-Ejector						

The objective of this study is to develop a method capable of revealing the relationship between a vehicle's configuration and requirements for problems like small supersonic transport design where little historical guidance is available, thus giving the designer greater insight into the impact of these important early decisions on project goals.

V.   Problem Approach

Though each of the new variations on the original Genetic Algorithm discussed previously provided important benefits for different problems, none of them could be directly applied to the problem as stated in the previous section. The MOGAs available in literature require excessive computer resources for computationally expensive objective functions and cannot handle subjective evaluation criteria, while the Interactive GAs are unable to account for qualitative characteristics that can be calculated by computer analyses.

Previous work by the author[25] to combine MOGAs with a parallel, variable fidelity strategy similar to Lim's resulted in a multi-objective algorithm that required fewer function calls than the methods available in the literature but did not yet incorporate user preferences into the design space search. Since past experience has shown that omitting engineering judgment from the optimization process can result in infeasible designs, this was felt to be a prime area for improvement.

F. Incorporation of expert input into design optimization

Takagi's research[15] has shown that human evaluators become fatigued long before performing even 1000 subjective evaluations during an IGA optimization run. It became apparent early in this research that the most direct approach, adding a measure of user satisfaction with the design as an additional objective to the already 8 objective design problem, would not be an acceptable solution since even parallel MOGAs typically require more than 10,000 evaluations to locate the Pareto frontier. The MOGA requirement for exponential population size scaling with the number of objectives meant that the number of objectives considered had to be kept to a minimum during the IGA procedure, since if too many individuals are displayed for subjective evaluation during an IGA run it can overwhelm the user. To reduce the number of objectives to a minimum, all of the quantifiable criteria were aggregated via a goal attainment metric, resulting in a 2-objective frontier showing the tradeoff between achieving the user's quantifiable goals and the level of subjective satisfaction with the design.

In order to fully incorporate designer preference into the optimization procedure, a graphical user interface was created that shows the population members currently being evaluated and queries the engineer for a rank of how "good" each individual is (Figure 10). To ease the burden on the evaluator, only five subjective fitness values were allowed: Bad, Poor, OK, Good, and Best. In addition to subjectively evaluating each design, the engineer is also allowed to update the goals and weights used to form the aggregate goal attainment metric, resulting in an IGA that is both "broad" and "narrow" according to Takagi's IGA classification system[15].
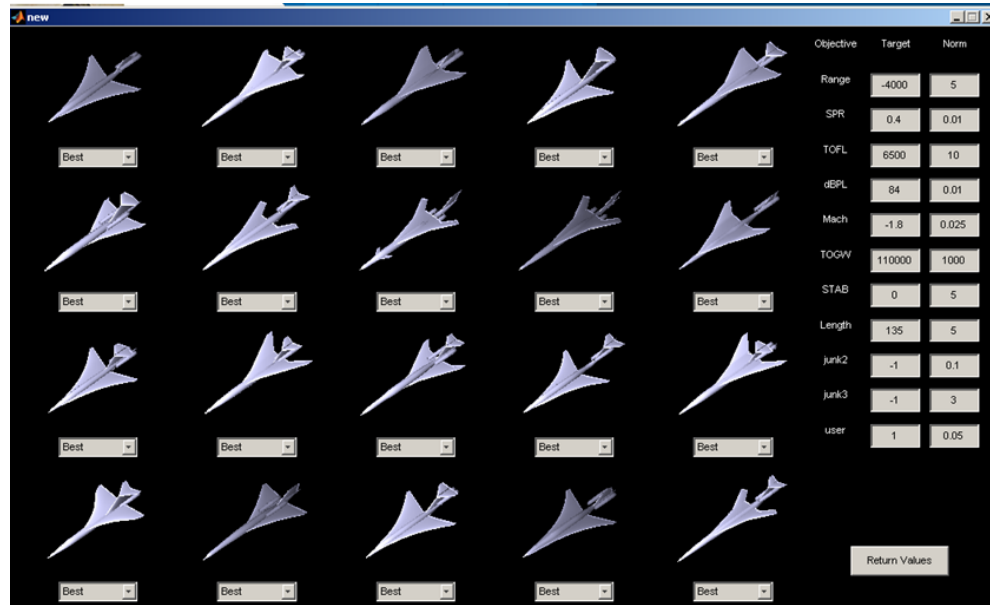

Figure 10 - GUI to obtain user input for the Interactive Genetic Algorithm

The mixed results of previous efforts to model human evaluation via neural networks or k-nearest neighbor interpolation led the authors to avoid using these techniques for this work, though incorporation of these methods is recognized as a promising area for future research. Instead, a new strategy was introduced where solutions from a Pareto front of the design problem that had been previously calculated were allowed to be injected by the user into the new Interactive GA population. Previous research has indicated that injecting known solutions into a population provides valuable genetic material, accelerates convergence, and can also be used to bias the direction of search[26].

VI.   Results

The IGA was allowed to run for twenty generations and required a total of 400 function evaluations, each of which consisted of querying the user for his or her subjective evaluation of the concept and also having the computer calculate performance metrics such as range, balanced field length, and boom loudness. Normally, 400 runs not be anywhere near enough to find good solutions, but the hand-picked injection of previously discovered solutions from a past GA run allowed promising candidates to be identified quickly. This injection was performed by using a graphical user interface[25] to explore the previously run GA's final population, and after locating an interesting airplane concept the designer was prompted to assign a subjective fitness value, after which the design was added to the current IGA population.

The Pareto frontier of the 20th generation contained three members (Figure 11); No solution with a "Bad" or "Poor" rating was present because they all had inferior goal performance and were dominated by the "OK", "Good", and "Best" designs.
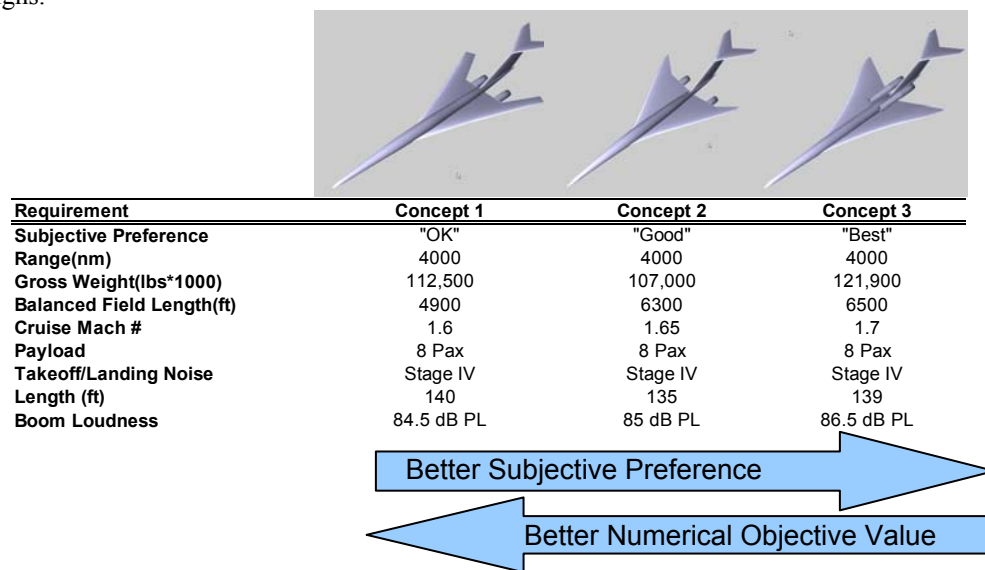

Requirement	Concept 1	Concept 2	Concept 3
Subjective Preference	"OK"	"Good"	"Best"
Range(nm)	4000	4000	4000
Gross Weight(lbs*1000)	112,500	107,000	121,900
Balanced Field Length(ft)	4900	6300	6500
Cruise Mach #	1.6	1.65	1.7
Payload	8 Pax	8 Pax	8 Pax
Takeoff/Landing Noise	Stage IV	Stage IV	Stage IV
Length (ft)	140	135	139
Boom Loudness	84.5 dB PL	85 dB PL	86.5 dB PL

Better Subjective Preference

Better Numerical Objective Value

Figure 11 - Pareto optimal solutions in the final IGA population

The "OK" solution was thus ranked because the author prefers to avoid using a variable geometry design if possible due to potential unmodeled cost and certification difficulties associated with these aircraft. The "Good" solution was viewed as slightly less desirable than the "Best" design because its under-wing mounted engines may cause shock coalescence in the far field, an effect not modeled by the linearized sonic boom code used for this study. No significant difficulties are expected to be encountered with the "Best" design, but it should be emphasized that the results of this interactive genetic search are dependent on how the user rates the designs and objectives; therefore different results would likely be obtained with another user providing the input.

VII.   Conclusion

This paper described a new hybrid quantitative/qualitative Genetic Algorithm that allows the designer to incorporate engineering judgment into the optimization process without over-constraining the problem. By using a

multi-criteria approach, the designer can view the tradeoff between performance as calculated by the computer model and the level of user satisfaction with the aesthetics, manufacturability, and other difficult to quantify criteria. Solutions obtained during previous multi-objective optimization runs were allowed to be injected into the interactive GA population in order to speed up convergence, and the results indicate that it is possible to guide the search towards a high performance region of the design space without significantly compromising user satisfaction with the concept. Future work will include more detailed analysis of the resulting configurations, an investigation of methods such as neural networks that may reduce the burden on the human operator, and incorporation of a module that will allow the designer to embed knowledge by actively modifying features during the evolutionary search process.

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